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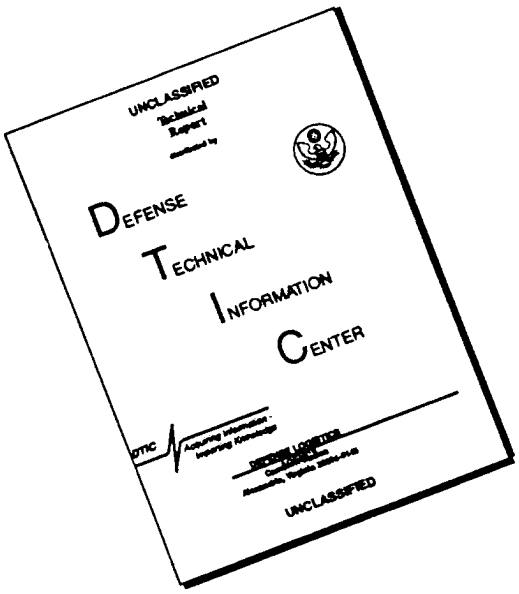

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Storage and Visualization of Spatial Data in a High-performance Semantic Database System

by

N. Rishe, D. Barton, and M. Sanchez

Technical Report #95-15

Storage and Visualization of Spatial Data in a High-performance Semantic Database System
FIU SCS Technical Report 95-15

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We are developing a prototype massively parallel database management system with applications to earth sciences. Our system will enable the highly efficient accumulation and retrieval of vast amount of general, scientific, and spatial data, utilizing a semantic/object-oriented approach to database management. One type of data in this system is a generalized spatial function — a function from a Cartesian product of several continuous and/or discrete domains into a Cartesian product of continuous domains and/or discrete domains and/or sets of semantic facts. This paper addresses issues of database storage of such functions, their querying, and visual presentation of results as multi-dimensional objects, particularly superimposition of two spatial functions in a 3-D display.
Keywords: semantic databases, spatial data, high performance, massive parallelism, scientific data, earth sciences databases, object-oriented databases, spatial queries, visualization, generalized spatial functions, spatial function superimposition.

1. INTRODUCTION

Earth science database applications have three essential needs:

- strong semantics embedded in the database so as to effectively handle the complexity of information
- storage of spatial, image, and other non-conventional data
- very high performance facilitating massive data flow

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Abundant evidence demonstrates that semantic/object-oriented databases can better satisfy the first two needs than relational databases. We are developing a highly parallel database machine based on the semantic/object-oriented approach that will also satisfy the third need — high performance.

Our research aims to significantly improve the usability and efficiency of highly parallel database computers and machine clusters (tightly networked groups of machines). Our prototype database management system will have substantial advantages over current database machines, due to:

- *Usability.* Our object-oriented system is based on the Semantic Binary Model of databases, unlike most current database systems, which are mainly based on the Relational Model. The use of semantic models ensures better logical properties: friendlier and more intelligent generic user interfaces based on the stored meaning of the data, comprehensive enforcement of integrity constraints, greater flexibility, and substantially shorter application programs.

  Semantic databases represent information as a collection of objects and relationships between these objects. The Semantic Binary Model of databases is a semantic model with object-oriented features [Rishe-92-DDS]. Data items related to objects can be of arbitrary size, multi-valued, or missing entirely. We have applied this approach to various types of data, including scientific and multi-media data. Semantic objects are not required to be identified by keys. An object may belong to many categories at the same type. Inclusion of categories determines inheritance of properties.

- *Efficiency.* Our system will be more efficient than existing database machines. This higher-efficiency goal can be attained by exploiting the system's understanding of the data's semantics and due to the higher abstraction level. The algorithms and prototype system that we are developing are highly efficient for both small and massive numbers of processors equipped with separate memories and storage devices. In particular, the use of the semantic model allows better exploitation of parallelism, by providing a means of distributing data among these processors in a way which is invisible to both database programmers and database users. We are developing algorithms and prototype software for the outer levels of the system (intelligent query processors and optimizers, content accessibility), as well as inner-level storage management. These algorithms will then be combined into one high performance system, with a very efficient representation of temporo-spatial and fuzzy data. Data is stored in highly-compressed form while allowing efficient and flexible retrieval.

This paper presents our theory and algorithms associated with one of the data types in our system: a *generalized spatial function* — a function from a Cartesian product of several continuous and/or discrete domains into a Cartesian product of continuous domains and/or discrete domains and/or sets of semantic facts. For example, ocean temperature is a function $f:X \times Y \times Z \times T \times O \rightarrow R^2 \times$ Factsets, where $X \times Y \times Z \times T$ is the space-time continuum and O is a discrete set of observation stations that reported measurements. Thus, $f(x,y,z,t,o)=(s,i)$, where s is a segment of temperatures (e.g., 50 degrees plus or minus 0.01 degrees) and i is a set of semantic facts. Another example is remote sensing (photography) of ocean color by the SeaWiFS satellite.

The spectrum of problems we have addressed concerning this data type includes:

1. Highly-efficient basic queries, including "inverse" queries (e.g., "Where is the temperature of about 70 degrees?")

2. Compact lossless storage

3. Compact lossy storage, particularly by approximating function values.

4. Efficient complex queries

5. Load balancing between processors and storage units

6. Visual presentation of query results as animated movies.

7. Visual presentation of query results containing two spatial functions of the same space as a 3-D overlay. For example, ozone layer thickness represented as elevation is superimposed with temperature represented as color.

2. RELATED WORK

Spatial and scientific databases have attracted the attention of many researchers. The proper statistical analysis of spatial and spatiotemporal data is critical to the success of any scientific study which uses such data. Cressie [Cressie-91] provides an extensive coverage of the current theories and methods used for spatial analysis, with some discussion of spatiotemporal methods. Our system will support these types of analyses, although the statistical procedures themselves are not part of our project.

A long-term goal of the JGOFS project [Flierl&*al.*-93] is to establish strategies for observing changes in ocean biogeochemical cycles in relation to climate change. A distributed approach is used in that project, where the data are not gathered into a central archive but rather reside at the originator's site. An object-oriented database system is developed for this purpose.

It is necessary to develop management tools that offer both the functionality required by a scientific environment and an interface that feels natural and intuitive to the non-expert [Ioannidis&*al.*-93]. A desktop Experiment Management System has been proposed as the interface between the experimental scientists and the data [Ioannidis&Livny-92].

The use of "layered database technology" to support scientific applications is suggested in [Shoshani-93]. It allows to provide interfaces to various levels for different scientific applications.

Research has been done on object-oriented data management systems for physical scientists [Hachem&*al.*-92]. The current goal of the Gaea project is to construct a prototype which permits integration of heterogeneous and complex datatypes in geography [Hachem&*al.*-93].

One of the ways to provide database support for high performance scientific applications is to create a special language for describing, finding, and accessing data by applications programs [Pfaltz&French-93]. The main goal is to interface many different computing environments to a common, persistent data space [Pfaltz&*al.*-88].

[Smith&*al.*-93] considers models using a large and heterogeneous collection of datasets. The problem of coupling several complex models arises in the application of spatially-distributed models of water, sediment and solute transport in the Amazon basin. A high-level Modeling and Database Language (MDBL) is suggested.

The need of using data from different sources arises in scientific applications. For example, the use of object-oriented databases for this purpose in the domain of computational chemistry is discussed in [Cushing&*al.*-92], and [Cushing&*al.*-93].

The SEQUOIA 2000 project ([Stonebraker-93], [Stonebraker&*al.*-93]) is designed for global change research. Management, storage and access to massive amount of data, are considered in that project.

Some interesting problems appear in medical applications of database technology. One of them is management of large repositories of image, text, and scientific information generated by academic medical research centers. Another one is the integration of different independent database systems which already exist in many specialized branches of medicine. These problems as well as the extension of traditional object-oriented data models into the temporal domain for accurately representing the data stored in medical image databases are considered in [Cardenas&*al.*-93] and [Chu&*al.*-92]. Visualization methods for query results and handling of 3-dimensional spatial data sets created from 2-dimensional medical images are investigated in the QBISM project [Arya&*al.*-93].

3. GENERALIZED SPATIAL FUNCTIONS

This section defines a new data type: a generalized spatial function.

Consider spatial functions that map a Euclidean space into values: f: $R^n \rightarrow R^m$ (where R is the continuum of real numbers). For example, ocean temperature is an $R^4 \rightarrow R$ function of latitude, longitude, depth, and time.

In some spatial applications, the function's domain may include discrete dimensions. For example, if *Observers* is a discrete set of observing devices then the perceived ocean temperature is $R^4 \times \text{Observers} \rightarrow R$.

In some spatial applications, each point in space is assigned not only certain values but also other arbitrary information, which can be generalized as a set of facts. Let *Factsets* be the set of all finite sets of facts. Let D be a discrete domain. A **generalized spatial function**:

$$\text{f: } R^m \times D^n \rightarrow R^k \times D^p \times Factsets^j$$

where m>0, n>=0, k>=0, p>=0, are integers, and j is 0 or 1.

For example, if facts can be observed as associated with certain space-time regions then the ocean temperature is: $f : X \times Y \times Z \times Time \times Observers \rightarrow Temperature \times Factsets$

In observation of natural phenomena one needs to distinguish between raw and processed/interpreted views. A *raw view* is a discrete set of measurements as reported by measurement devices. Raw views contain noise. Further, raw views are typically expressed in terms of the activity of the measuring devices rather than in terms of the actual coordinates of the observed phenomena, i.e. the coordinates are not geo-calibrated. *Processed/interpeted views* attempt to estimate and approximate the actual attributes of the observed phenomena, by what we call generalized spatial functions. The broad community of users of spatial data

needs only processed views. A small group of scientists uses the raw views to derive processed views by applying various theories. These scientists keep improving and fine-tuning such theories. Consider, for example, the problem of translating a satellite's motion coordinates and device angles into the Earth surface coordinates of the measured phenomenon. The techniques of doing so, and their precision, are open for improvement, especially in the polar zones. The raw spatial data cannot be smoothened and must be available in full detail. The processed spatial data represents an estimation of the natural phenomenon, and, therefore, has properties of typically continuous functions defined over the space continuum. The raw spatial data may coexist in a database with processed data, but different techniques may be used for storage and retrieval of the two types.

As an example, consider the ocean color observations to be made by the NASA SeaWiFS satellite. Figure 3-1 represents the semantic schema that we use in our experimental database to store and access raw SeaWiFS data. Actually, this not the immediate satellite data but rather derived by a straightforward algorithm, not involving the intelligence and ambiguity of estimating the actual color in ocean-surface coordinates.

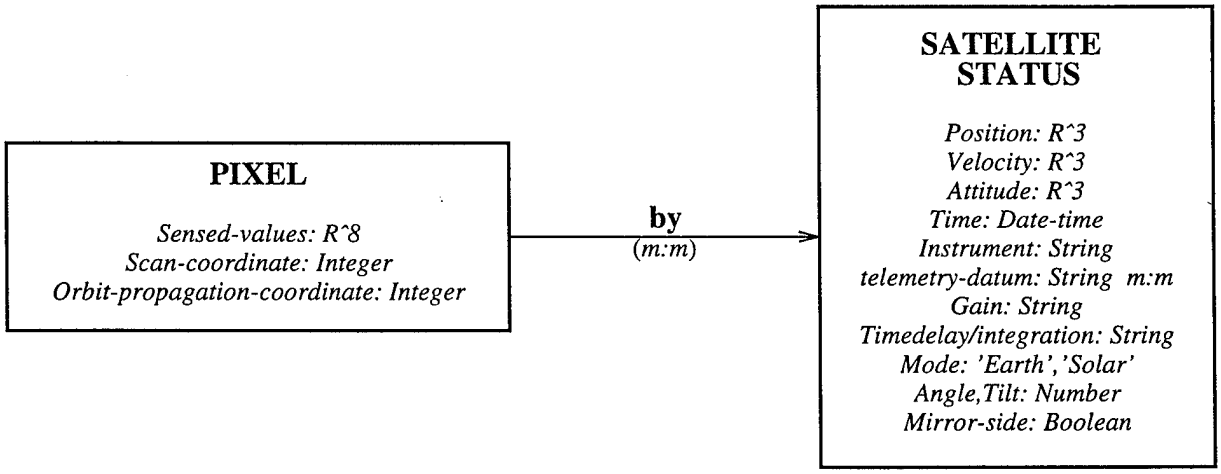

Figure 3-1. SeaWiFS: Logical Schema of Unpacked Raw Data. Only some pixels directly correspond to some status records; for each such status record only some of the data from the list is available.

The schema of Figure 3-1 uses the semantic modeling notation of [Rishe-92-DDS], which is briefly explained here. The category *PIXEL* is the set of pixels, in orbital coordinates, for which color recording is taken. The attributes *Scan_coordinate* and *Orbit_propagation_coordinate* are of type Integer and define a matrix of pixels. For each pixel, there are 8 color values for 8 different bandwidths (they are taken by eight devices on board). This vector of eight values is represented by the attribute *Sensed–values* of type R^8. The category *PIXEL* contains the actual measurements as taken. What geographical points on the ocean surface does a given pixel correspond to, and what is the real color of those points, is an issue of non-trivial and imprecise analysis. Such analysis is aided by the other information in this schema. Some pixels are associated with satellite status data by the relation *BY*. This relation is many-to-many. It is not a total relation, meaning that some (actually, most) pixels do not have any satellite status data explicitly associated with them

(but such data can be inferred from that associated with nearby pixels; we say that a status record is explicitly associated with a pixel if the record was transmitted by the satellite immediately before the pixel). Since there is a variety of satellite status records, transmitted at various times, each status record may contain some, but not all, of the following information. The *Position* and *Velocity* attributes are vectors of three numbers each, representing the satellite's position and velocity. *Angle* and *Tilt* refer to the aiming of the lens. Their type is Number, referring to any number representable by a finite string of digits. We do not have any precision or magnitude restrictions on real numbers [Rishe-92-IB]. *Telemetry_data* is a multi-valued attribute of type *String*, i.e. one satellite status record can have a set of strings of telemetry data. *Mode* is an attribute of an enumerated type. *Time* is an attribute of the type Date-time, implemented as arbitrary numbers, standing for the number of seconds since a certain date-time t_0. (It allows any decimally-expressible fraction of a second.)

Figure 3-2 is the semantic schema of processed SeaWiFS data, further interpreted to expand the discrete measures to be reflective of the space-time continuum that they represent. It defines generalized spatial function over the three-dimensional continuum of ocean surface latitude longitude and time. Most users are interested only in this interpreted information, not in the raw data. The following section discusses an efficient implementation of this "infinite" data structure.

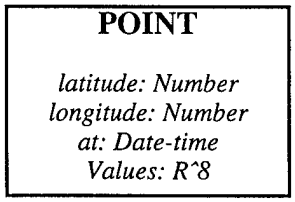

Figure 3-2. SeaWiFS: Logical schema of interpreted data. There is an infinite continuum of points.

4. PHYSICAL STORAGE OF GENERALIZED SPATIAL FUNCTIONS

4.1. Goals

Logically, spatial functions are defined over a continuum. At the physical level, we represent spatial functions by a finite set allowing approximate interpolation of the function. We notice that the spatial function itself represents an estimation of a natural phenomenon, derived from some finite raw data. Therefore the values interpolated from its physical representation need not be more precise than said estimation.

As an example of a characteristic problem and its solution, let us consider ocean temperature. The ocean can be regarded as a four-dimensional Euclidean space of longitude, latitude, depth, and time. Thus, temperature T is a function $T(x,y,z,t)$. Additionally, there is a discrete dimension of observation sources, which may disagree between them. Thus, the temperature function may have five arguments: $T(x,y,z,t,s)$. If δ is the precision of

knowledge of temperature at a point, then the assertion of the database is that the actual temperature is between $T(x,y,z,t,s)-\delta$ and $T(x,y,z,t,s)+\delta$. In some application, δ is not a constant but depends on the point, in which case we have generalized spatial functions producing for each point a segment of possible temperature values: $T(x,y,z,t,s)\pm\delta(x,y,z,t,s)$. If the database represents this temperature knowledge fully, we call it a *fully lossless* representation of the interpreted spatial data. If this knowledge is approximated in the database by a value segment $T'(x,y,z,t,s)\pm\Delta$ containing the segment $T\pm\delta$ and Δ is not substantially greater than δ, then we call this representation *approximately lossless*. In this case, the difference $\Delta-\delta$ is the degree of approximation. As will be discussed below, we can vary the degree of approximation as a function of the required compactness and efficiency of the database. If for some points (x,y,x,t,s), $T'(x,y,z,t,s)$ is outside the segment $T(x,y,z,t,s)\pm\delta$, then the representation is *lossy*. When the generalized spatial function is continuous (and it typically is for interpreted natural phenomena, except for boundary conditions) we can have a highly compact and efficient fully- or approximately lossless representation, as will be shown later in this paper.

The following are examples of some queries that are asked about this function:

(Q_1) Find the temperature for a given 5-dimensional point (whether it is a point of actual measurement or interpolated). This is the most basic query.

(Q_2) a more complex query: find the temperature of a four-dimensional space-time point independent of the observation source, obtained by weighing the different sources according to their known reliability, etc.

(Q_3) find the average temperature of a given arbitrary segment of space-time body.

(Q_4) delineate space-time ranges where the temperatures are between given t_1 and t_2.

Logically, we assume that we have a virtual infinite database containing all the observed measurements and the interpolated points. The following specifications delineate this virtual database's schema, graphically depicted in Figure 4-1.

- ☐ *OBSERVATION-SOURCE* — category (The set of entities measuring ocean temperature)
- ☐ *description* — attribute of *OBSERVATION-SOURCE*, range: *String* (*1:1*) (The identifying description of an observation source)
- ☐ *reliability* — attribute of *OBSERVATION-SOURCE*, range: *0..1.00* (*m:1*) (A number between 0 and 1)
- ☐ *POINT-VALUE* — category (The infinite set of all pairs of space-time points and their possible temperature values)
- ☐ *point* — attribute of *POINT-VALUE*, range: *R^4* (*m:1*) (Vector in space-time)
- ☐ *temperature* — attribute of *POINT-VALUE*, range: *Number* (*m:1*) (In degrees Kelvin)
- ☐ *produced* — relation from *OBSERVATION-SOURCE* to *POINT-VALUE* (*m:m*) (A many-to-many association between point-values and observation sources that collected raw data which upon processing and interpretation yielded the point-value)

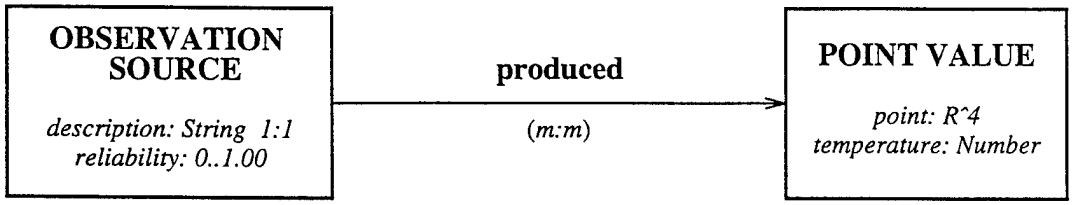

Figure 4-1. Infinite virtual database

4.2. Linear Hyperquadrant Data Structure

The infinite logical view of Figure 4-1 can be mapped into a compact actual database of Figure 4-2. Later in this paper we will introduce further refinements of compactness and efficiency of this database.

In the database schema of Figure 4-2 we represent the space-time continuum as a hexadecimal tree of hyper-quadrants. We utilize the well-known theory of linear quad-trees of [Gargantini-82], which we extend to multi-dimensional generalized spatial functions and adapt to semantic databases. Our further refinements of this data structure are discussed in the next section.

Let δ be the precision of knowledge of the generalized spatial function and Δ be the desired precision of knowledge representation in the database, $\Delta \geq \delta$. In order to simplify this discussion, we will use the terms of the above temperature examples (whereby extending the results to an arbitrary generalized spatial function with an arbitrary number of dimensions will be obvious). Further, we will assume that Δ and δ are constants over the observed space-time. Generalization to the case when they are varying functions over the space-time is easy.

First we define the partitioning of a four-dimensional continuum into a tree of hyper-quadrants labeled by hexadecimal strings. The relevant space-time is bounded and, therefore, it can be embedded in a huge hyper-rectangle, S. Now, let us halve all the edges of S, thus partitioning S into 16 hyper-quadrants touching each other at the center of gravity of S. Let us label them by the 16 hexadecimal digits: 0, 1, 2, 3, 4, 5, 6, 7, 8, 9, a, b, c, d, e, f. Each of them can in turn be partitioned into 16 smaller hyper-quadrants, denoted by two hexadecimal digits, *e.g.* #7 is partitioned into 70, 71, 72, 73, 74, 75, 76, 77, 78, 79, 7a, 7b, 7c, 7d, 7e, 7f. Each of them can be further partitioned, and so on. The inclusion between hyperquadrants is defined by their label, so no pointers would be necessary: hyperquadrant h_1 contains hyperquadrant h_2 if and only if label(h_1) is a prefix of label(h_2).

We note that a mathematical point (x,y,z,t) in space-time is a hyperquadrant of zero size; its label is an infinite hexadecimal string *microhyperquadrant*(x,y,z,t). (We are introducing this only for the purpose of analysis below, not for actual storage in the database).

Now, a four-dimensional temperature function of space-time $T:R^4 \rightarrow$ R can represented, up to the desired degree of precision Δ, as a finite set of non-overlapping hyper-quadrants of various sizes by the following recursive process: if the function varies on a given hyperquadrant h_1 more than allowed by the desired precision Δ, then partition h_1 into sixteen smaller hyperquadrants.

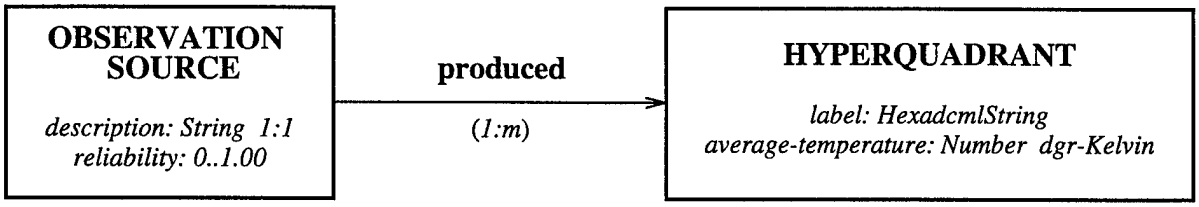

Figure 4-2. Finite representation of a generalized spatial function Temperature by a tree of hyper-quadrants

Now, the query Q_1 becomes:
T(x,y,z,t,s)= get m.TEMPERATURE where (s PRODUCED m and m.LABEL is a prefix of *microhyperquadrant*(x,y,z,t)))

To allow efficient computation of queries like Q_1, the hyperquadrants of a given source s_0 can be stored at the physical level as a subfile HYPERQUADRANTS[label,temperature]. This subfile is a B+-tree ordered by labels. The following explains why Q_1 can be resolved in just one access to the disk.

The index level of the B+-tree contains the first labels of each physical block of records. Therefore, the index level is several orders of magnitude smaller than the data level. For example, if 1000 records [label,temperature] fit in each block, then the index level is 1000 times smaller than the data level of the B+-tree. Thus, we can normally assume that the index level resides in the memory (if this assumption were invalid, then the number of disk accesses to perform Q_1 would go from one to just two accesses). Since for s_0 the space-time was partitioned into a set of *disjoint*, varied-sizes hyperquadrants, there is only one hyperquadrant whose label l_1 is a prefix of *microhyperquadrant*(x,y,z,t). The label l_1 is thus the lexicographically greatest stored label less than *microhyperquadrant*(x,y,z,t). This record must reside in the data block whose first label l_0 is the lexicographically greatest index-level label below *microhyperquadrant*(x,y,z,t). Thus the index level will point to exactly one block containing the answer to query Q_1. Since one cannot possibly resolve a query requiring information from a disk in less than one disk access, the above-described algorithm is optimal.

This data structure also allows highly efficient computation of queries Q_2 and Q_3. To efficiently resolve query Q_4, which delineates areas having a temperature in a given range t_1 to t_2, we store an inverse index subfile INVERSE[temperature,label] which is a B+-tree ordered by temperature. The answer to Q_2 is the set of records *INVERSE*$[t,l]$ where $t_1-\Delta \le t \le t_2+\Delta$. This is the contiguous fragment of the file INVERSE specified as a B-tree range from $t_1-\Delta$ to $t_2+\Delta$. If the number of records in the output is substantially less than can fit into one data block then the query can normally be resolved in just one disk access. If the number of records in the output is large enough to fill n blocks then the query can normally be resolved in $n+1$ disk accesses. This is either the optimum or very close to the optimum.

We should note that Temperature, like all the numbers in our Semantic DBMS is of arbitrary precision and magnitude, and must be represented by a compact bit string of varying length. Further, in order to allow B-tree indexing and certain other operations, these varying-length strings must be lexicographically orderable preserving the meaningful order of numbers. To accomplish this, we use the order-preserving varying-length compact number

encoding defined in [Rishe-92-IB].

All the subfiles of the database are placed in one database file. In the high-performance version of our system, this file is partitioned between many disks and processors.

4.3. Polynomial Approximation Data Structure

Still further reduction in the storage of a generalized spatial function, e.g. the Temperature function, can be obtained if we sample the space-time not into very small bodies of approximately constant temperature (i.e. varying within a given Δ only) but into larger bodies whose temperature can be represented by an analytical function. For such bodies we will store the average temperature as well as an optional polynomial describing the offset in terms of the points' coordinates. This can also achieve a fully lossless representation without a great storage overhead.

Consider a generalized spatial function $T(x,y,z,t)\pm\delta(x,y,z,t)$, representing interpreted (processed) knowledge of a natural phenomenon, e.g. the ocean temperature. Since our knowledge of Nature is never exact, we can normally assume that $\delta>0$. We produce a fully lossless representation of this function by a finite set of non-overlapping hyper-quadrants of various sizes by the following recursive process:

Let h be a hyperquadrant; let $center(h)$ be its center point; let $average(h)$ be the average temperature of h, defined as:

$$average(h)=\frac{\int\limits_{(x,y,z,t)\in h} T(x,y,z,t)\,dx\,dy\,dz\,dt}{volume(h)}$$

Let $P_h : R^4 \rightarrow R$ be a minimal-degree polynomial function of the four-dimensional space such that:

$$(*)\quad \forall(x,y,z,t)\in h: \left|(average(h)+P_h((x,y,z,t)-center(h))-T(x,y,z,t)\right|\le\delta(x,y,z,t)$$

For a polynomial P, let $length(P)$ be the sum of lengths of representations of the coefficients of the polynomial P. For example,

$$length(<2x^2+1.35178>)=length(2)+length(1.35178)=1+6=7.$$

Let $Maxlength\le\infty$ be a global constant limiting the length of polynomials we wish to store in the database.

Recursive procedure on hyperquadrant h : If a polynomial P_h satisfying (*) does not exist, or cannot be found efficiently, or if the length of minimal such polynomial exceeds Maxlength, then partition the hyperquadrant h into 16 contained hyperquadrants and recursively apply the procedure to each of the 16 hyperquadrants.

To further reduce the database's size, we combine hyperquadrants into clusters if they can use the same polynomial. A cluster is one hyperquadrant or a set C of hyperquadrants (typically adjacent but not necessarily of the same size) with a polynomial P_C such that:

$$\forall h\in C: \forall(x,y,z,t)\in h: \left|(average(C)+P_C((x,y,z,t)-center(C))-T(x,y,z,t)\right|\le\delta(x,y,z,t)$$

where $center(C)=\dfrac{\sum\limits_{h\in C} center(h)}{cardinality(C)}$, $\quad average(C)=\dfrac{\sum\limits_{h\in C} average(h)\times volume(h)}{\sum\limits_{h\in C} volume(h)}$

Figure 4-3 defines a schema of the resulting compact and efficient database.

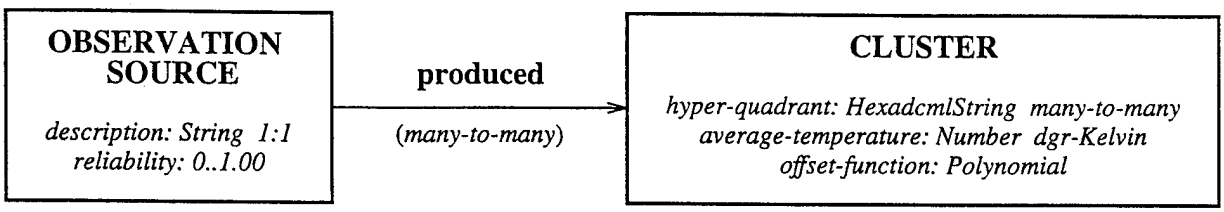

Figure 4-3. One cluster has several hyper-quadrants and an optional offset interpolating function

Further, to avoid storing the polynomial in every cluster, we can have a global default linear polynomial, which will be implied for those clusters for which no polynomial has been assigned in the databases. Now, Query Q_1 becomes:

$T(x,y,z,t,s) =$

get m.AVERAGE-TEMPERATURE+ (m.OFFSET-FUNCTION)((x,y,z,t) – center(m))
where s PRODUCED m and m has a hyper-quadrant h which is a prefix of the hexadecimal string *microhyperquadrant* (x,y,z,t).

In our database implementation, the above query will normally be resolved in just two disk accesses, assuming there is only one observation source covering the point (x,y,z,t).

Queries Q_2, Q_3, and Q_4 are also very efficient in this database.

4.4. Visualization

Generalized spatial functions can represent information stored in the database as well as information contained in the output of a query. Here are some examples. The aforementioned query Q_4 (to find segments of space-time for a given temperature range t_1 to t_2) produces a generalized spatial function. The *identity* query Q_0 copies an entire stored spatial function into output. Query Q_5 produces the temperature function $T_s : R^4 \rightarrow R$ for a given observation source s. Query Q_6 produces source-averaged surface temperature data for the Caribbean Sea surface, $T_{Carib} : R^3 \rightarrow R$. Query Q_7 produces both surface temperature and ozone thickness data, (Temperature,Ozone): $R^3 \rightarrow R^2$. Query Q_8 produces a discrete spatial function which for each city and each month gives the monthly average temperature, Citytemp: *Cities*×{1..12}→*Temperature*. Query Q_9 produces a function f_8 : Cities × Time → Temperature × Ozone × Factsets. This function, for every city c and every moment in time t, gives the temperature, the ozone thickness, and the set of facts describing the events that were happening in the city at time t (i.e. events that started at or before t and ended after t). Here, *Cities* is a discrete domain and *Time* is a continuum. Query Q_{10} produces uninterpreted SeaWiFS measurements in discrete orbital coordinates, together with information on satellite and lens positioning when making the measurements:

SW: OrbitPropagation × Scan × Time × Band → Color × Factsets

In this section we discuss two methods we employ for visualization of such query results. The first one, animation, in not conceptually novel, but is interesting especially in

terms of performance ramifications in our system, as well as certain presentation enhancements that we introduce. The second, novel, method is the 3-D function superimposition.

4.4.1. Animation

Consider a query whose output is a three-dimensional function f: $R^3 \rightarrow R$, e.g. *temperature* (*latitude* ,*longitude* ,*time*).

We can display this function by mapping any two of the dimensions on the screen and translating the third dimension into a frame sequence. This can be seen as a movie with VCR-like controls — speed, pause, direction, rewind, etc. — as well as with zoom control.

Our systems also provides the user with pull-down menus or buttons to dynamically select a geographical display projection type for spatial functions. The projection types currently supported are: mercator, homolographic, stereographic, sinusoidal, orthogonal, and orthographic.

To accommodate factsets in the visual presentation, e.g. the factsets produced in queries Q_9 and Q_{10}, we will be able to perform the following: when the user clicks at a point on the screen the system displays facts concerning that point.

When a query produces a spatial function of more than 3 dimensions, e.g. f: R^5 -> R, the viewing user will have buttons to dynamically freeze any dimensions and select two screen dimensions and one frame-sequence dimension.

Efficient support of animation requires very fast execution of spatial queries by the database server and very fast delivery of the results to the user. In our prototype, a cluster of database server machines is connected to user workstations via an ATM network, capable of simultaneously delivering 150 megabits per second to each user. The animation was implemented by David Barton, Elma Alvarez, and Martha Gutierez. Illustrations 1 through 11 show snapshots of the user's screen.

4.4.2. Function superimposition

Here, we would like to describe a novel visualization method that we employ: spatial function superimposition.

Consider a query whose output consists of two spatial functions of the same two-dimensional subspace. Example: the ozone layer thickness and the ocean temperature of a particular region on a particular date. The user posing this query desires to see correlation between the two functions. In visualization of this query we represent this output as a virtual reality 3-dimensional image, where the first function is mapped into elevation and the second into color. In our prototype system, the user can explore this image using virtual reality goggles: the user wearing such goggles can look at the image at various angles and positions. The computer senses the angle and the position of the person viewing the image via infra-red signaling, which the system uses to display appropriate views in relation to the user's position. The depth illusion that the system implements works by displaying a stereo image: two quickly alternating images, each of which corresponds to the particular image that each eye would see if the query visualization were a 3-dimensional object in the real world. The goggles complete the effect by synchronously blocking the view of one of the eyes with an

LCD lens, fooling the brain into thinking that it is a real 3-dimensional object. A user without such goggles can still benefit from this data visualization method by rotating the image on the screen and looking at various pseudo-3D projections — an example of this is in the last Illustration 12.

Consider now a query whose output is a pair of spatial functions of a *three*-dimensional subspace (F:$R^3 \rightarrow R^2$). Example: the ozone layer thickness and temperature of an ocean region during a given time interval — a query posed by a user interested to see how the temperature/ozone correlation changes in time. We present F as a sequence of functions F_t: $R^2 \rightarrow R^2$. For each t, F_t is viewed as a 3-D relief. The sequence of images F_t is viewed as an animated video with VCR-like controls (speed, play forward, rewind, frame by frame viewing, etc.), as well as with image controls (zoom, viewing angle, etc.).

Illustration 12 depicts F_0, a snapshot of F at a time t_0 — we froze the time to render a static 3-D image. In this example, the continents are colored brown, the ocean is colored from blue to red according to the surface temperature, and the ozone thickness is mapped into the relief's elevation. The ozone layer thickness happened to be measured when the hole in the ozone layer is apparent in the Antarctic region, as seen by a sharp slope at the left side of the snapshot. (This is a snapshot of a relief built on top of an orthogonal projection of the Earth; the image has been rotated and put in a perspective as if viewed from the Pacific Ocean westwards — this way the relief is clearly seen even without the help of the aforementioned 3-D goggles.)

The superimposition visualization program was written by Louis Florit. It is a part of the query visualization subsystem of our prototype semantic spatial database management system.

5. CONCLUSION

Our prototype for a massively parallel database management system is designed to efficiently realize complex queries on multi-dimensional spatial-temporal data and efficiently deliver the results to the user in an intelligible visual perspective. These direct and inverse relations between varied measures and geolocated objects are integral to deciphering and understanding Nature. The multi-dimensional visualization of highly intricate relations over massive amount of data aids in the rapid interpretation of complex and extended measures by domain scientists. We are certain that these features of our system are indispensable in effectively analyzing the enormous and imposing amount of scientific data quantifying our environment.

Acknowledgment.

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Projection Data Rotation Date Cloud Exit

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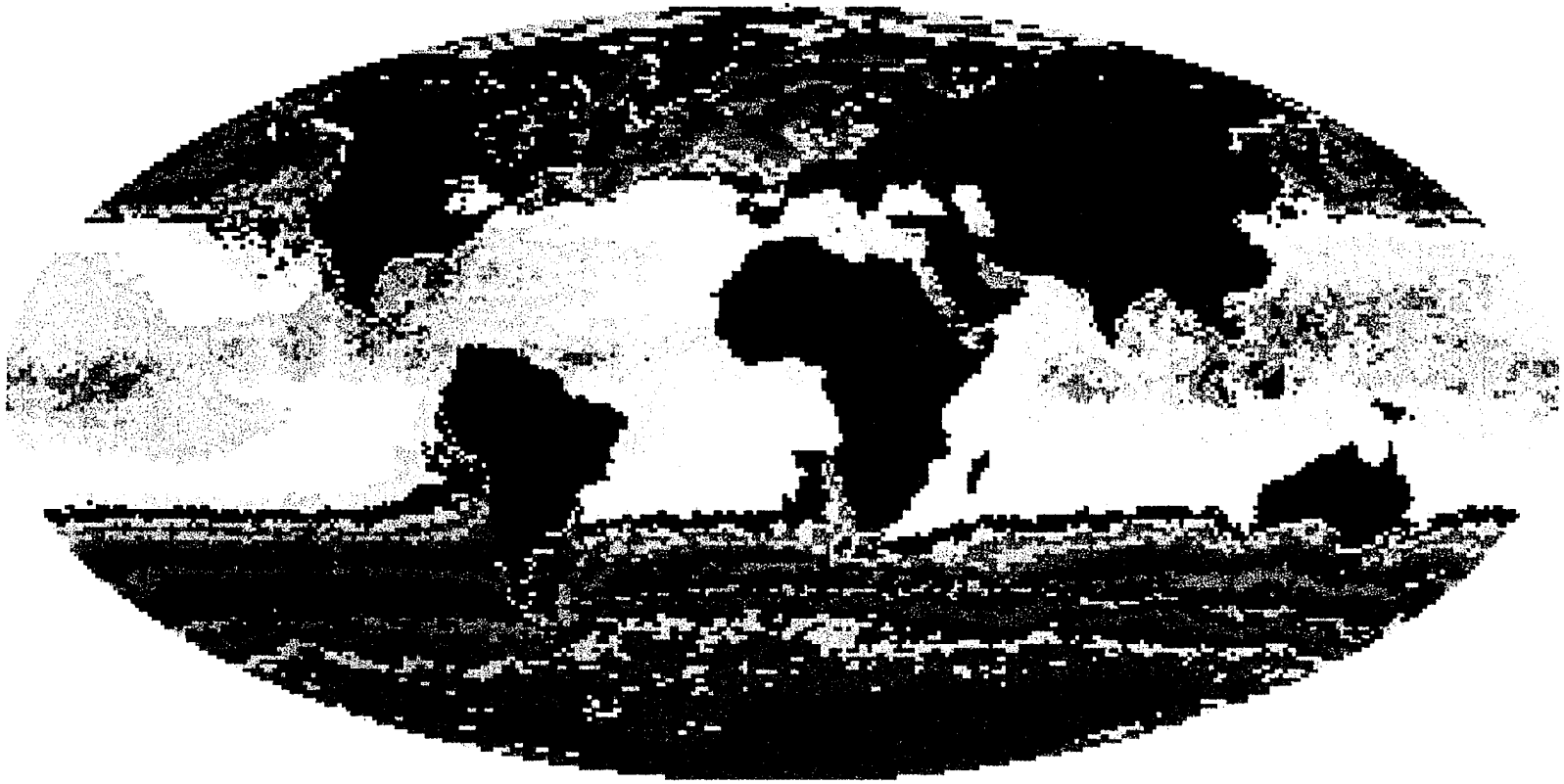
- Orthogonal
- Sinusoidal
- Stereographic
- Homolographic
- Mercator

Date: 8/ 1/1987



Temperature in °C

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Projection Data Rotation Date Cloud Exit

- Orthographic
- Orthogonal
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- Stereographic
- Homolographic
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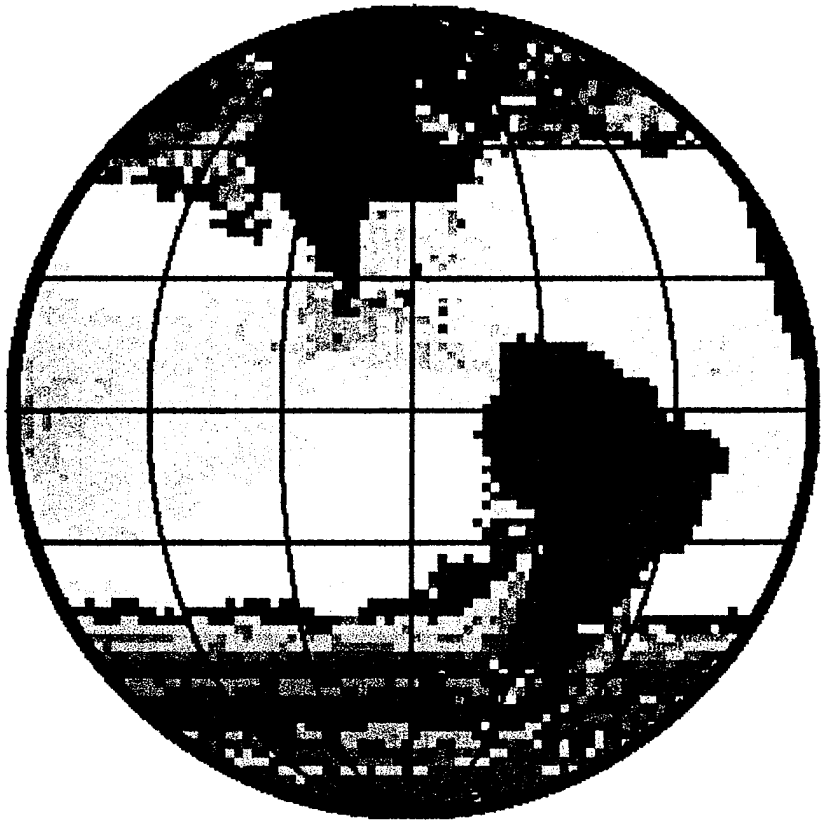
Date: 6/21/1987



Temperature in °C

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Projection Data Rotation Date Cloud Exit

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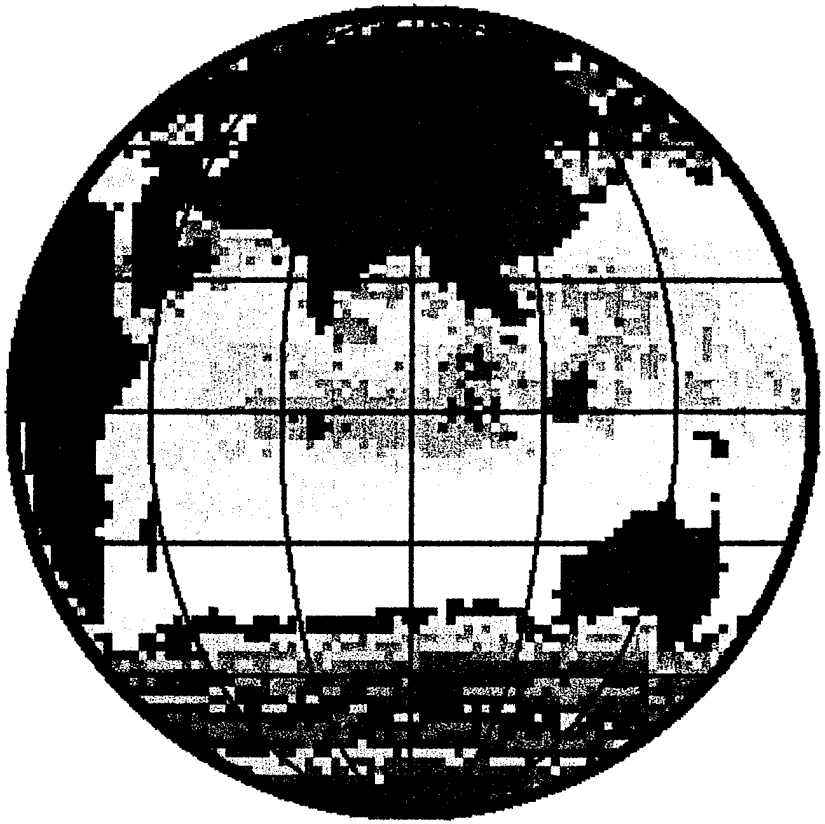
Date: 6/14/1987



Temperature in °C

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Projection Data Rotation Date Cloud Exit

- Orthographic
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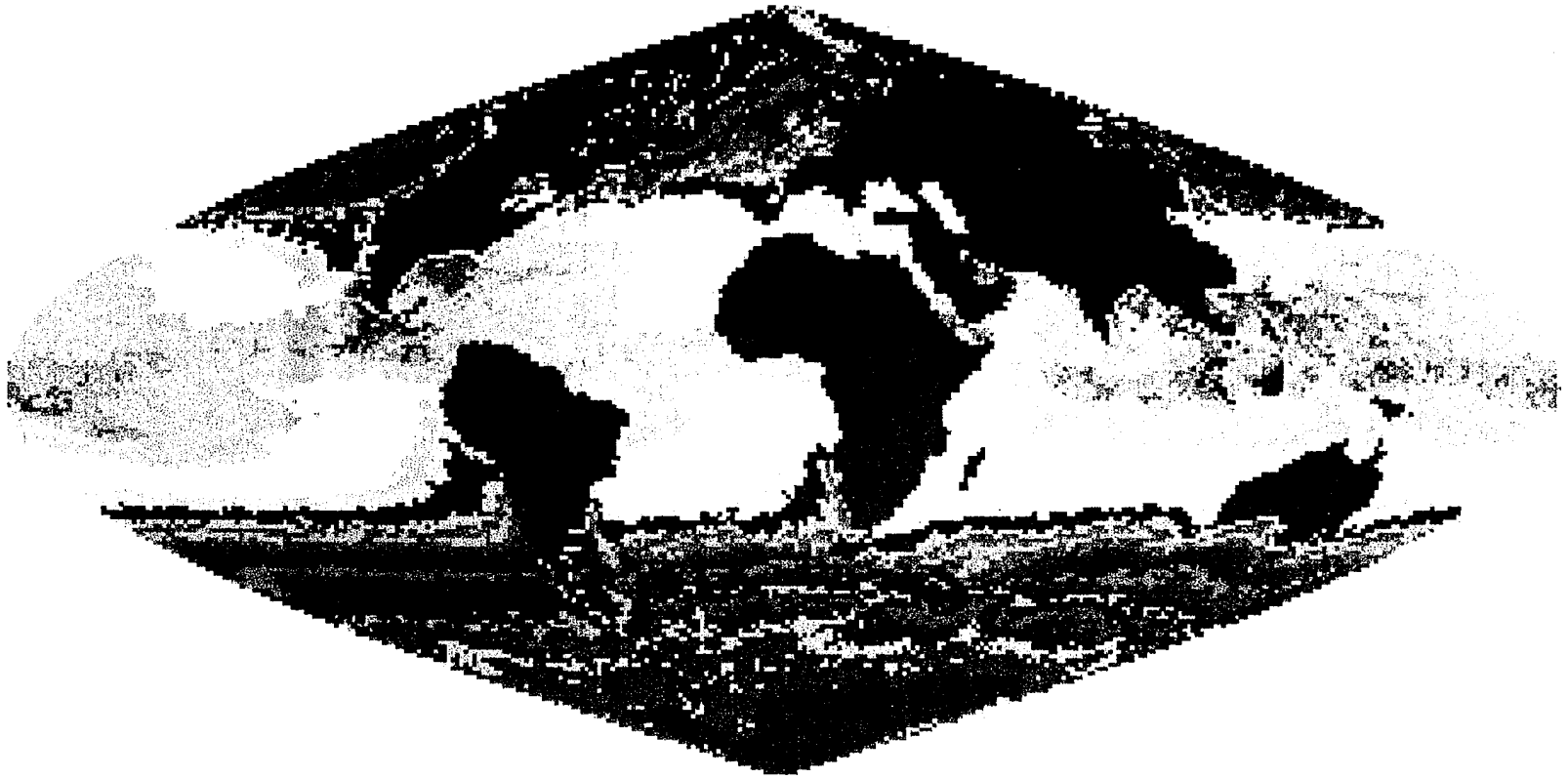
- Stereographic
- Homolographic
- Mercator

Date: 7/11/1987



Temperature in °C

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- Mercator

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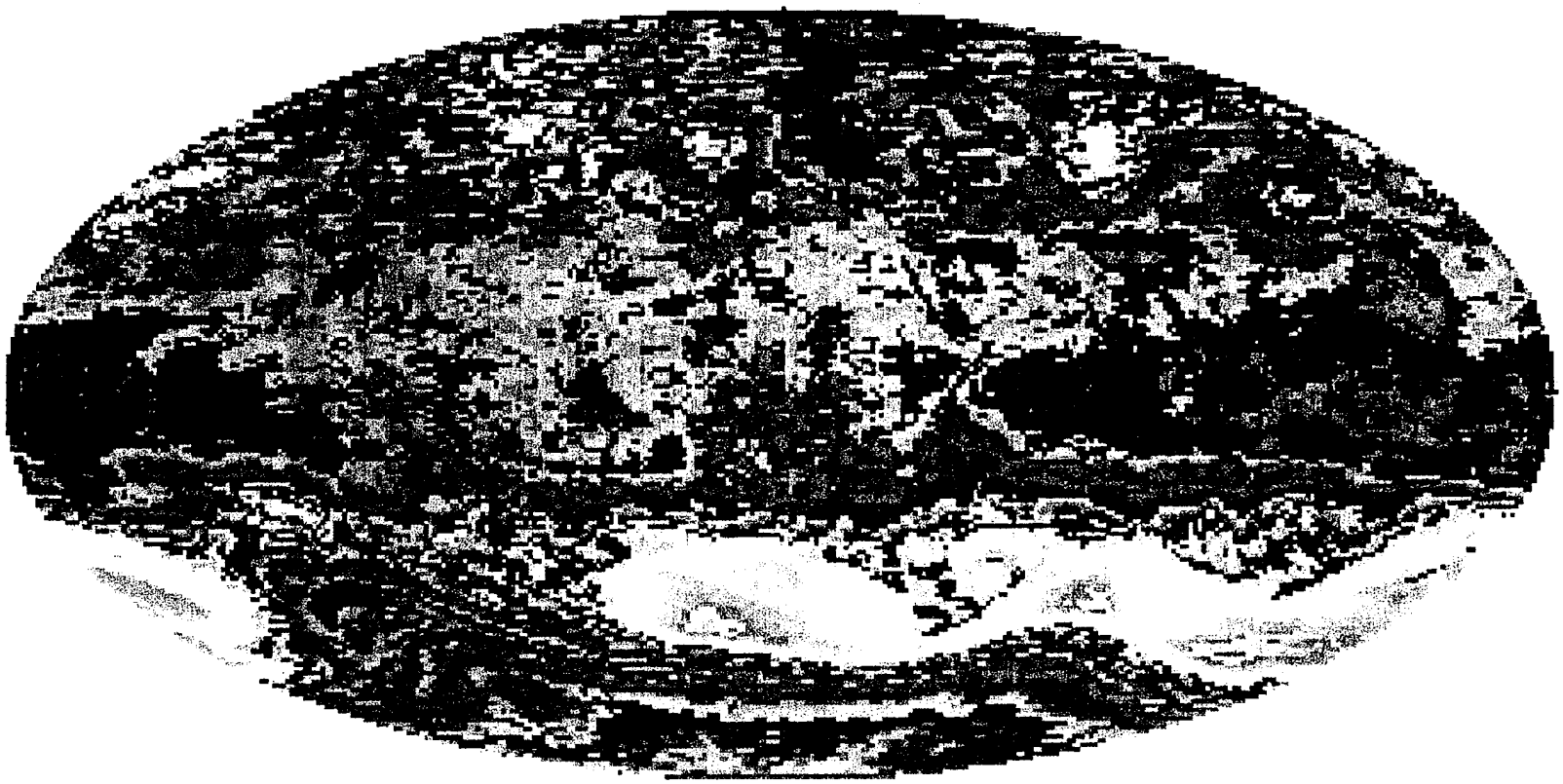

Ozone Layer
in Dobson Units

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174..185
186..197
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234..245
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270..281
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294..305
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318..329
330..341
342..353
354..365
366..377
378..389
390..401
402..413
414..425
426..437
438..449
450..461
462..473
474..485
486..497
498..509
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522..533
534..545
546..557
558..569
570..581

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Projection Data Rotation Date Cloud Exit

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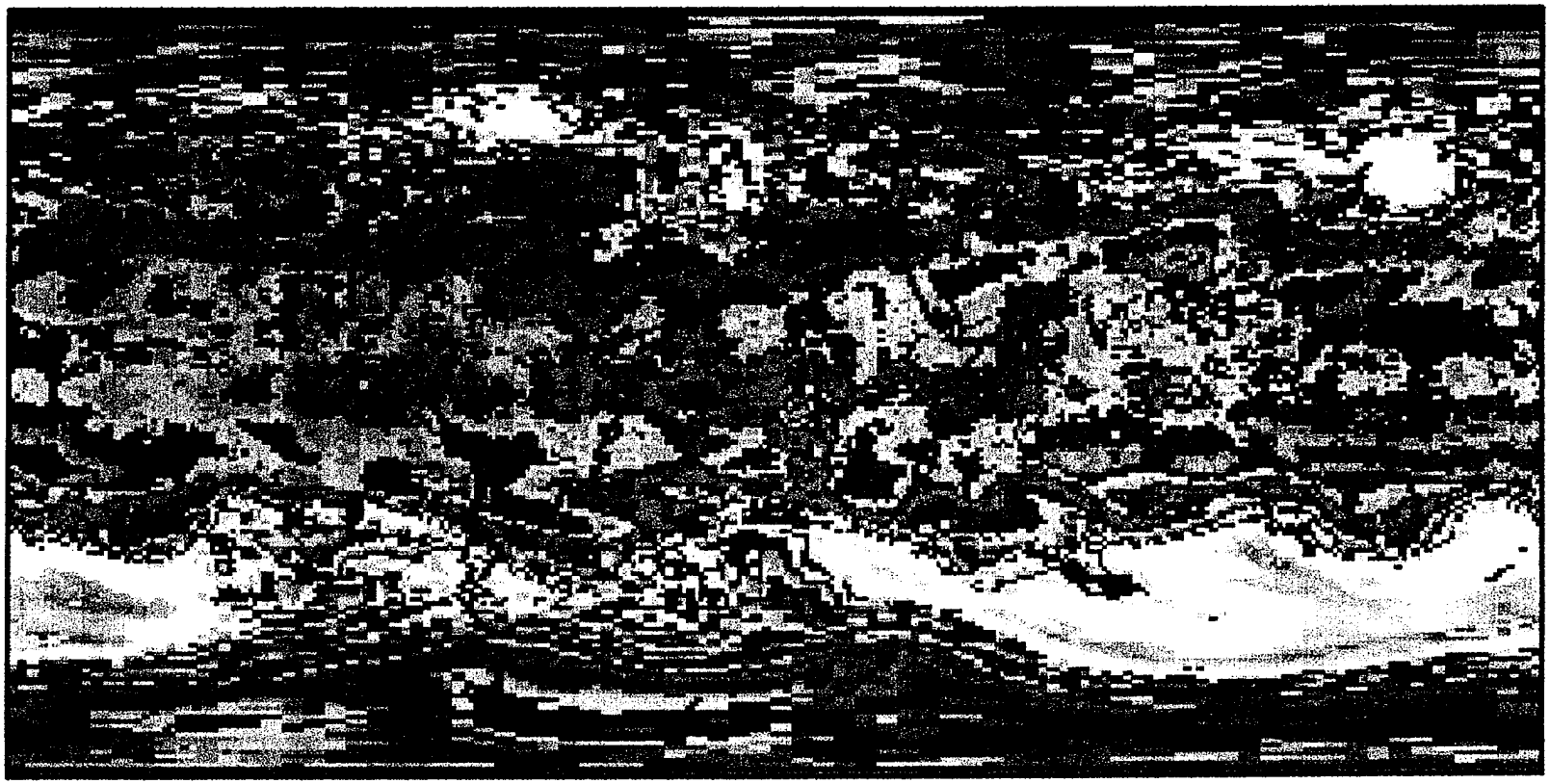
- Orthogonal
- Sinusoidal
- Stereographic
- Homolographic
- Mercator

Date: 9/21/1992



Ozone Layer
in Dobson Units

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- 486..497
- 498..509
- 510..521
- 522..533
- 534..545
- 546..557
- 558..569
- 570..581

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Projection Data Rotation Date Cloud Exit

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- Orthogonal
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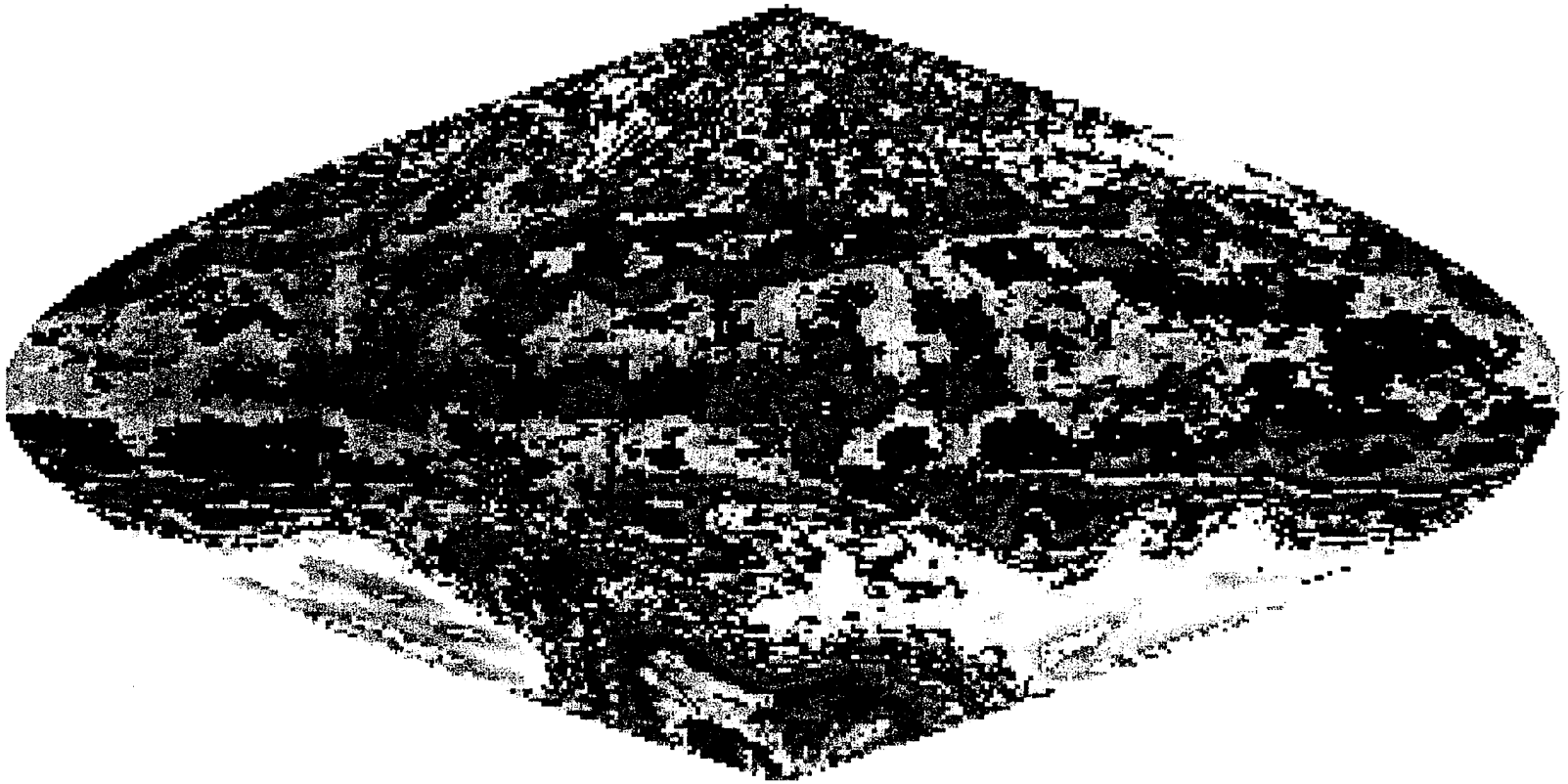
- Mercator

Date: 9/23/1992



Ozone Layer
in Dobson Units

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Projection Data Rotation Date Cloud Exit

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Ozone Layer
in Dobson Units

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Projection Data Rotation Date Cloud Exit

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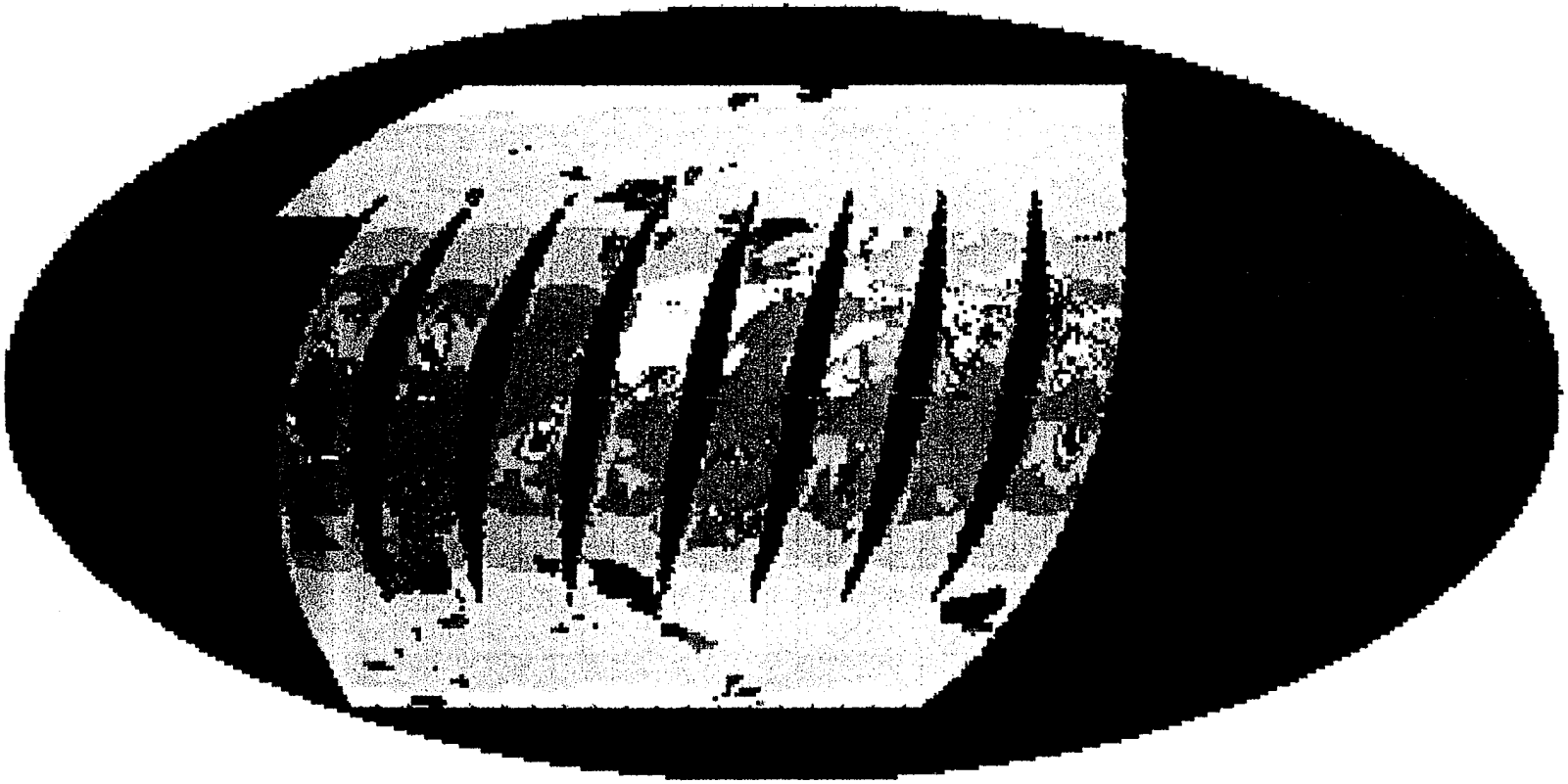
- Homolographic
- Mercator

SeaWiFS

Date: 3/ 5/1995



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Projection Data Rotation Date Cloud Exit

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SeaWiFS

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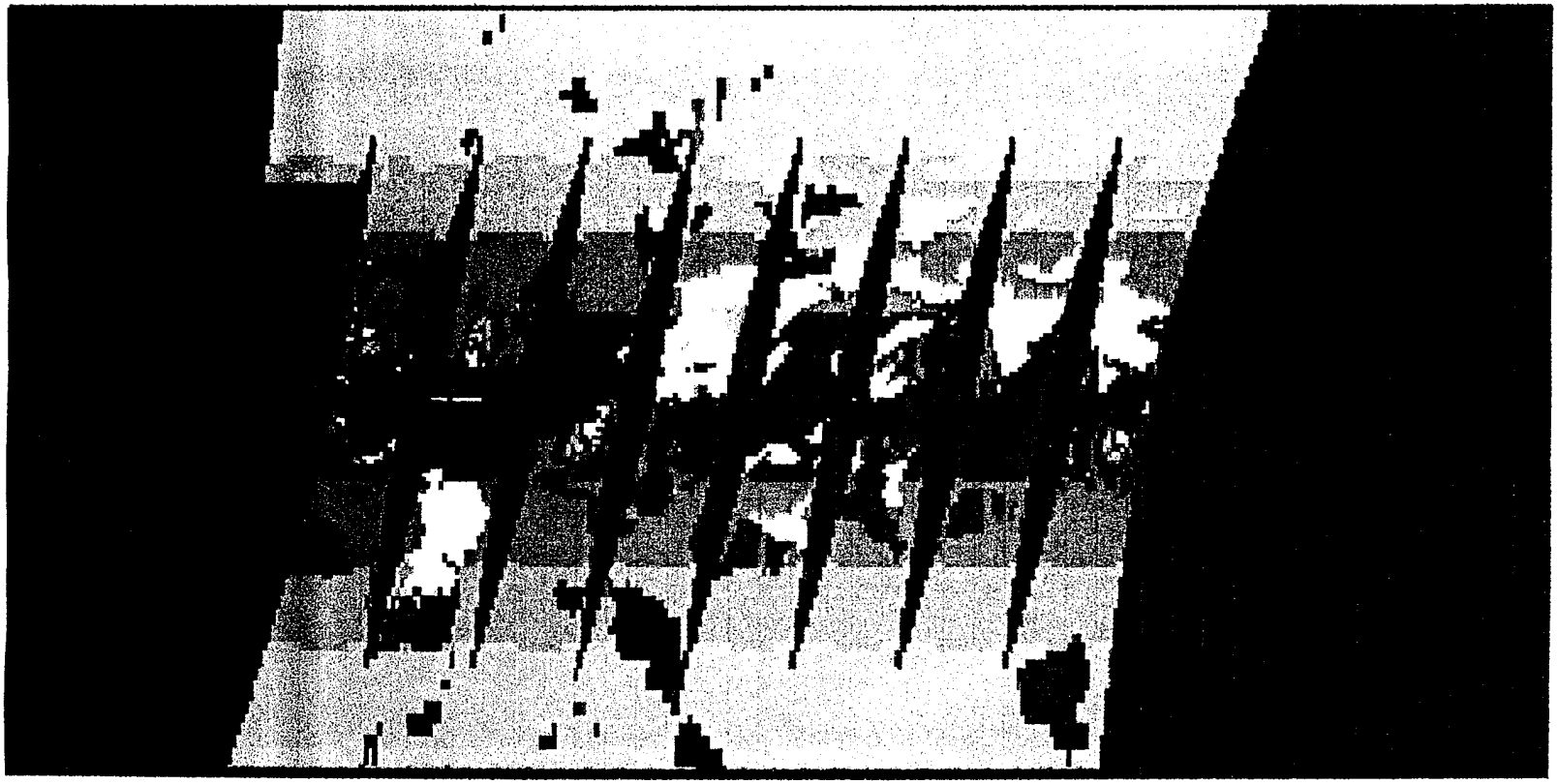

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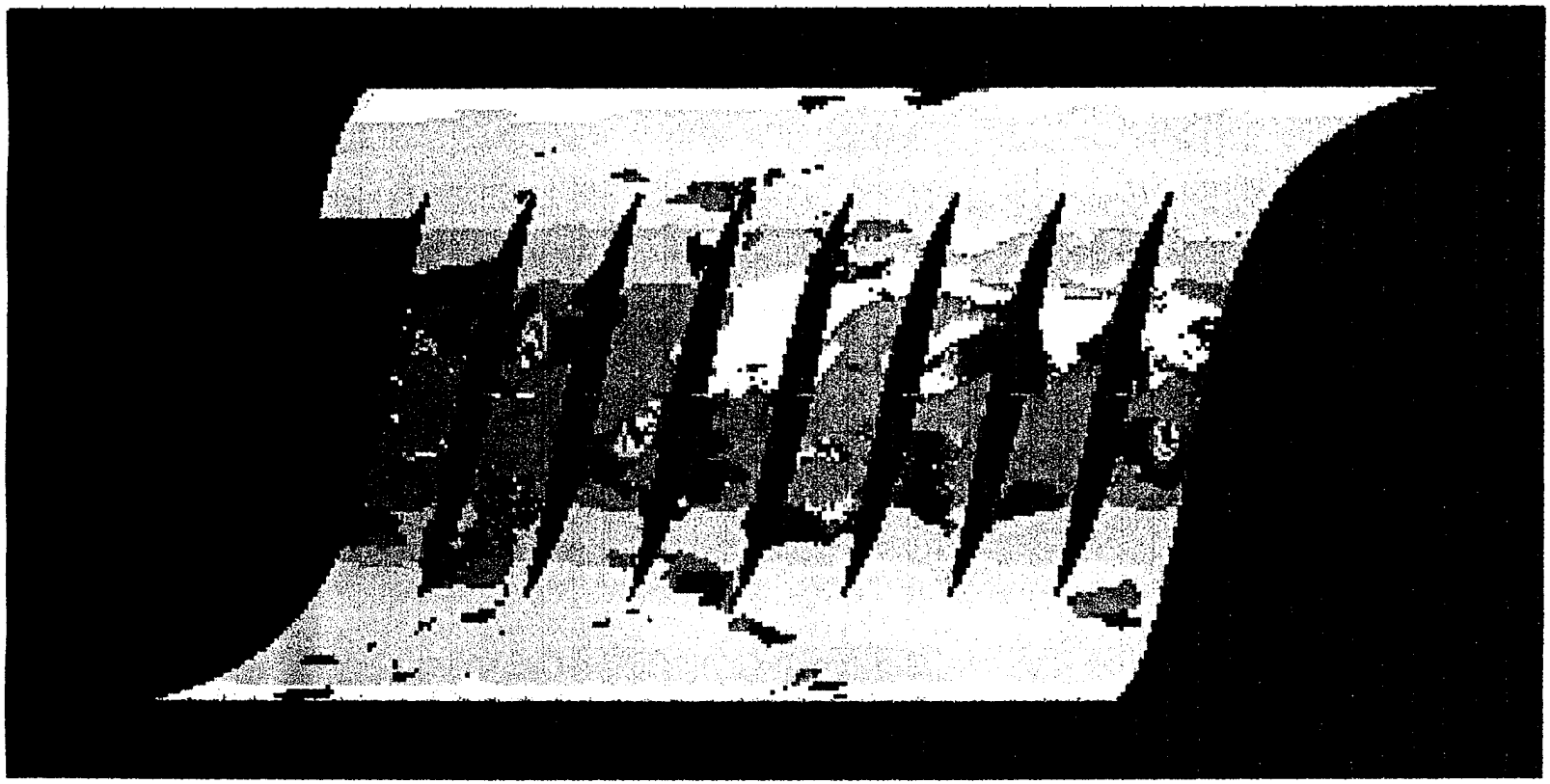
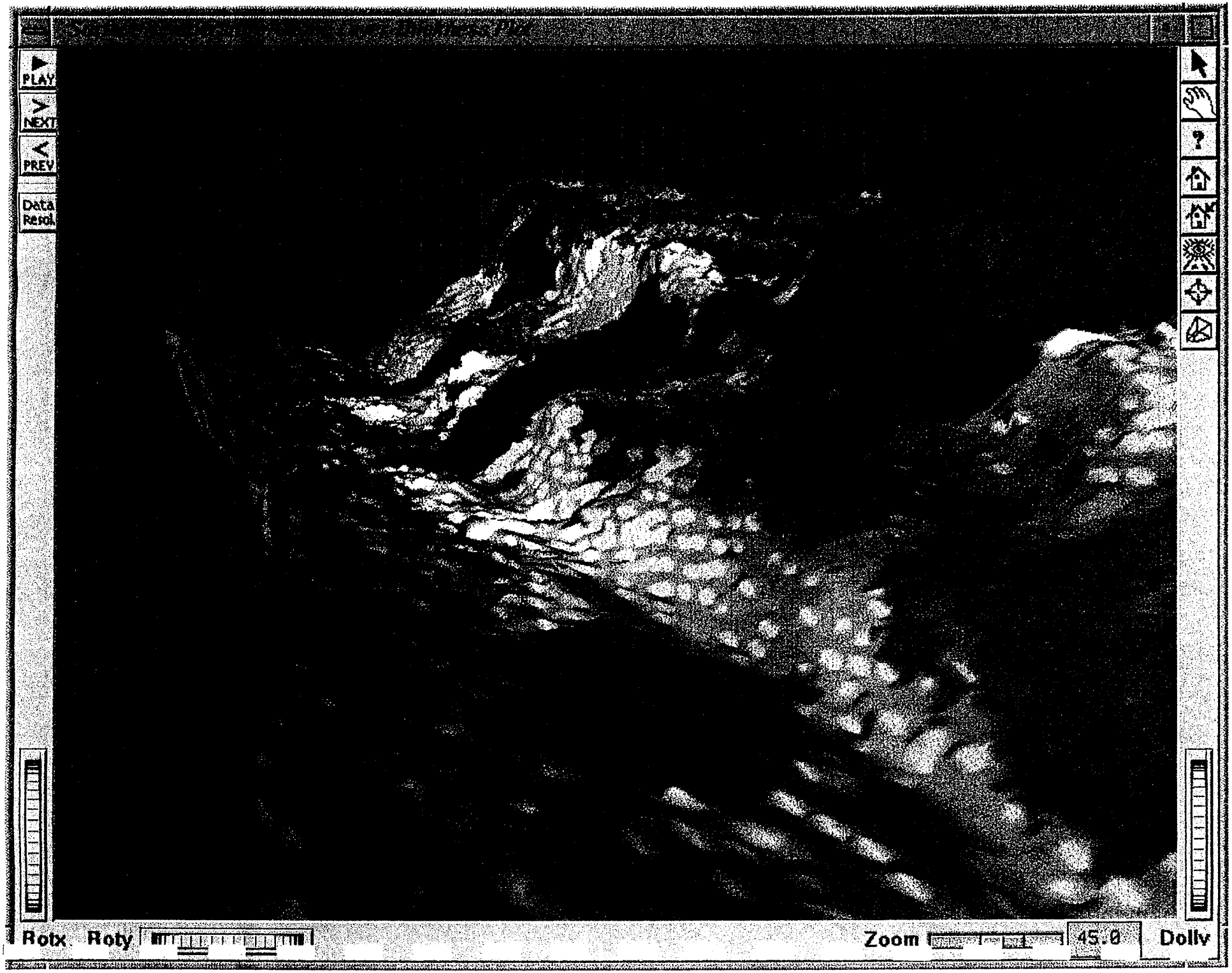
SeaWiFS

Date: 3/ 6/1995




PLAY
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Data Resol
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